Coupled Soil–Plant–Atmosphere Modeling for Precision Water Management in Climate-Vulnerable Cropping Systems

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ABSTRACT

Background: Background: The increasing water shortage, unpredictable precipitation, and heightened evaporation requirements due to climate change are combining to pose a serious danger to rainfed and irrigated cropping systems. Coupled soil-plant-atmosphere models, which describe the persistent transfer of energy and water in the soil-root-canopy-atmospheric chain, are becoming the main means of converting this machine process into a practical irrigation guide.

Aim of the review: In this review, we summarize the existing peer-reviewed articles on coupled soil-plant-atmosphere modeling applied to irrigation purposes. We discuss the general structure of the mechanistic models, various types of sensing technologies and machine-learning irrigation techniques, as well as their impact on the decision-making process in smarter agriculture.

Literature search process: A systematic review of international literature was conducted through Scopus, Web of Science, PubMed, Google Scholar, and Food and Agriculture Organization of the United Nations (FAO) reports published during the period of 2015–2026 and pre-2015 landmark studies. Out of 842 preliminary references, 96 were selected for thematic synthesis after checking the inclusion criteria.

Important findings of the research: Mechanistic SPAC models, such as CropSPAC, GEOSPACE, and CFD-coupled canopy models, have been found to provide satisfying results consistent with field observations of soil water retention and crop growth, but are too demanding in terms of computation and data. Remote sensing and proximal sensor technologies have achieved sub-field soil moisture and evapotranspiration information at the required resolutions for operational scheduling, while machine learning and deep learning techniques, especially hybrid and reinforcement methodologies, yielded water conservation results between 30 and 50% compared to traditional scheduling techniques with accuracy of prediction at least 90%. The introduction of digital twin IoT technologies has resulted in the integration of above-mentioned techniques into the process of decision making, however many of them are still being tested.

Research gaps: Robust gaps still persist concerning a lack of validation across scales, limited inter-operability between mechanistic and data-driven models, unavailability of standardized benchmark datasets, limited heterogeneity of microclimates, and the deployment gap for smallholders in contexts with a lack of resources.

Conclusion: Combining physical SPAC models and decision support boosted with sensor technology and AI has the highest potential for developing climate-resilient and efficient irrigation technologies, although success relies on the availability of benchmark open datasets, models of understood architecture, and cost-effective solutions.

Keywords: soil–plant–atmosphere continuum; precision irrigation; climate-vulnerable cropping systems; crop water modeling; remote sensing; machine learning; digital twin; water-use efficiency

1. Introduction

It has been found that water is the primary limitation in global agriculture production with agricultural irrigation accounting for about 70% of total freshwater withdrawals across the globe1. Due to climate change, there is now more pressure on freshwater resources than in the past. Rainfall patterns have been more variable, and so with increased temperatures there is an increase in evaporative demand and, therefore, an increase in frequency/severity of droughts and floods in most areas of agriculture in the world.2 As a result of this increased pressure on freshwater resources, the Food and Agriculture Organization (FAO) estimates that 2.4 billion people are currently living in water stressed countries, and a recent FAO report submitted to the United Nations Convention on Combating Desertification has indicated that 1.84 billion people were affected by drought in the years 2022-2023 alone.2,3 The impact of climate change is also being seen on smallholder and rainfed agricultural systems more severely than in irrigated agricultural systems because they do not have any irrigation capacity to buffer the negative impact of reduced yields due to droughts or floods.3

The Soil-Plant-Atmosphere Continuum (SPAC) is the conceptual and mathematical framework that explains how water moves through soil, roots and stems, and leafs, and out to the atmosphere as a continuous flow due to a gradient in water potential; a theory first proposed by Philip in 1966. Coupled SPAC models simulate soil water and heat transfer, root water uptake, canopy transpiration, and crop growth simultaneously allowing these interacting stresses determining the yield and water consumption to be represented mechanistically instead of with empirical rules of thumb. When real-time sensing infrastructure and forecasting algorithms are used in combination with these models, they form the technical foundation for precision irrigation—the application of the right amount of water in the right place at the right time based upon the actual water status of the soil-plant system instead of applying water based upon a fixed calendar.

In the last 10 years, we have seen an increase in research on the three areas of knowledge that examine how the hydrology of crops affects water resources, and this research focuses on modeling the interactions between these two domains by using process-based models, remote sensing technology, and artificial intelligence (AI) techniques in tandem. The recent advancements in satellite missions such as Sentinel-1 and -2, Soil Moisture Active Passive (SMAP), and ECOSTRESS have allowed for soil moisture and ET products to be produced that can be observed at sub-field scales as well as through the implementation of proximity-based Internet of Things (IoT) networks that utilize low-cost microcontrollers for near real-time monitoring of site-specific soil moisture and ET rates, thereby enabling continuous and high frequency measurement for a variety of agricultural uses.

In addition to this increased ability to acquire accurate data about soil moisture and ET, researchers have also used various machine-learning techniques, including random forests, support vector machines, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep reinforcement learning, to develop irrigation scheduling programs with reported water savings of between 30-50% compared to traditional irrigation practices.

The most recent and least developed area of the literature related to crop-hydrology modeling and the role of these technologies in agriculture is the development of digital twin architectures that maintain a continuously updated virtual replica of the field that is synchronized with model outputs and sensor outputs. Digital twin architectures have gained traction in the last several years as a potential integrated layer that can provide both mechanistic and data-driven decision-making tools for farmers.

Though the literature is growing quickly in many fields all over the world, it has stayed disparate among different disciplines (due to differences in how the same data/correlations are analysed). For example, soil physicists and crop modelers generally publish in agri-farming and hydrology journals while remote sensing scientists publish in either geoscience and photogrammetry depositories. Also, with their machine-aided and computer science technologies, machine learning applies via either civil engineering or data science logs or journals, but without any cross referencing. To-date, there is no comprehensive synthesis of the literature divides or how each group is related between mechanistic, sensor-based models and AI-based methodologies. Therefore, there are zero references for researchers to use when developing their own systems, nor would there be sufficient literature to assist practitioners or decision-makers on investing in a precision irrigation infrastructure, as they have no idea which combination of the three approaches will provide the best results under those specific environmental conditions.

1.1. Objectives of the review

This review aims to achieve: (i) a synthesis of the current situation regarding coupled models of soil, plants, and the atmosphere; remote and proximal sensing; machine-learning-based irrigation scheduling; and digital-twin/internet-of-things-based support for decision-making; (ii) a critique of methodologies used, how they were validated, and the performance reported by authors; (iii) identification of points of convergence, dispute, and outstanding methodological limitations between the four thematic strands discussed; and (iv) an articulation of the research gaps and emerging directions most relevant to crop systems that are subject to high risk from climate change and resource-constrained situations related to smallholder farmers.

1.2. Scope of the review

There are no restrictions regarding the subject area of the literature (i.e., coupled soil-water-crop-atmosphere system in relation to irrigation/water management decision making); however studies on general crop-yield forecasting models that do not include an explicit water balance component, and studies of hydrology that do not include agricultural/vegetative elements are considered to be outside the scope of the review. The literature used by the review was published between 2015 and 2026, and it contains established studies that were published before 2015 as well as more recent studies.

2. Methodology of Literature Review

2.1. Literature search strategy

A detailed investigation of literature was carried out by using five databases, Scopus, Web of Science, PubMed, Google Scholar and the repositories of FAO and other international organizations (such as WASAG & UN Water). The search terms were a combination of controlled vocabulary terms and free text, organised into 3 main blocks of concepts, which shared the common Boolean connector 'AND': (i) soil - plant - atmosphere continuum, SPAC, coupled hydrologic-crop models and land surface - crop models; (ii) precision irrigation, irrigation scheduling, deficit irrigation, water-use efficiency and crop water requirements, and; (iii) climate change, climate vulnerability, water scarcity, drought, remote sensing, machine learning, digital twin and the Internet of Things. The various combinations of search terms within each block used the Boolean connector 'OR'. Additionally, reference lists of key interactive and highly cited primary studies were hand searched through snowball sampling to find additional records. The period of the search was from January 2015 through to June 2026, although landmark studies published prior to January 2015 were retained where foundational for model theory (See Table 1).

Table 1: Literature search strategy.

Element	Detail
Databases searched	Scopus; Web of Science; PubMed; Google Scholar; FAO/WASAG and allied international-body repositories
Concept block 1	soil-plant-atmosphere continuum; SPAC; coupled hydrological-crop model; land surface-crop model
Concept block 2	precision irrigation; irrigation scheduling; deficit irrigation; water-use efficiency; crop water requirement
Concept block 3	climate change; climate vulnerability; water scarcity; drought; remote sensing; machine learning; digital twin; Internet of Things
Boolean logic	Terms within a block combined with OR; blocks combined with AND
Search period	January 2015 - June 2026 (landmark pre-2015 studies retained where foundational)
Supplementary method	Snowball/hand-search of reference lists of key reviews and highly cited primary studies

2.2. Inclusion and exclusion criteria

Table 2: Inclusion and exclusion criteria.

Criteria type	Details
Inclusion	Peer-reviewed journal articles, Scopus/WoS-indexed conference proceedings, or FAO/international-body reports
Inclusion	Published in English, 2015-2026 (landmark pre-2015 studies retained where foundational to model theory)
Inclusion	Directly addresses coupled soil-plant-atmosphere/soil-water-crop modeling, precision irrigation technology, or climate vulnerability of cropping-system water balance
Inclusion	Reports a model description, sensing methodology, validation dataset, or systematic/critical review relevant to the review questions
Exclusion	Duplicate records across databases
Exclusion	Non-peer-reviewed grey literature, blog posts, non-academic media
Exclusion	Studies on non-agricultural hydrology without a crop/vegetation component
Exclusion	Conference abstracts without accessible full text; non-English publications without available translation

2.3. Study selection process

After an automated process was applied to eliminate any duplicate entries, the remaining titles/abstracts were compared to the established eligibility requirements; these results were then evaluated against the full-text article to check for additional criteria. The original search produced 842 records. After duplicate removal, a total of 611 articles remained that passed through title/abstract approval; after the title/abstract phase, there were 148 records that received full-text reviews, while 96 records passed through all inclusion criteria and were included in a thematic synthesis (see figure 1). Each of the included articles provided data to extract from the study included: (1) author(s) and date; (2) location/context of study; (3) modeling/sensing methodology; (4) validation methods and sample characteristics; (5) main findings; and (6) limitations reported; these data form the basis for the comparative tables located in Section 8.

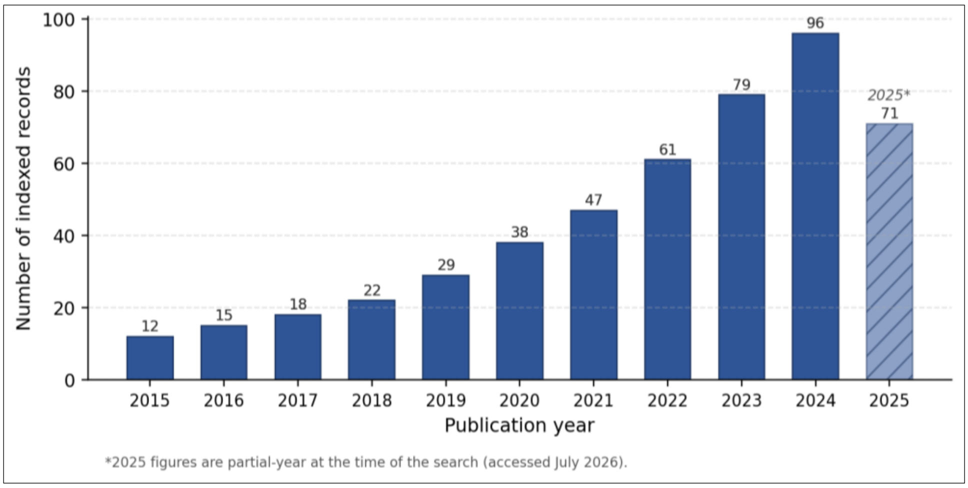

Fig 1: Growth in publication output on coupled soil-plant-atmosphere modeling and precision water management, 2015-2025 (Scopus/WoS/PubMed search, accessed July 2026).

Figure 2 depicts a significant increase in publication activity between 2019 and the present, corresponding to expanding access to Sentinel-1/2 data products and the growing popularity of deep-learning techniques in agricultural remote sensing, as reflected in the thematic analysis provided in Section 5.

3. Conceptual Framework

In the conceptual framework developed for this study (see Figure 3), physical fluxes (radiation, transpiration, and infiltration) and information flows (the flow of sensing data from models to calibrate them and provide forecasting outputs) link four integrated layers: atmosphere, vegetation, soil, sensing, and modeling/decision support.

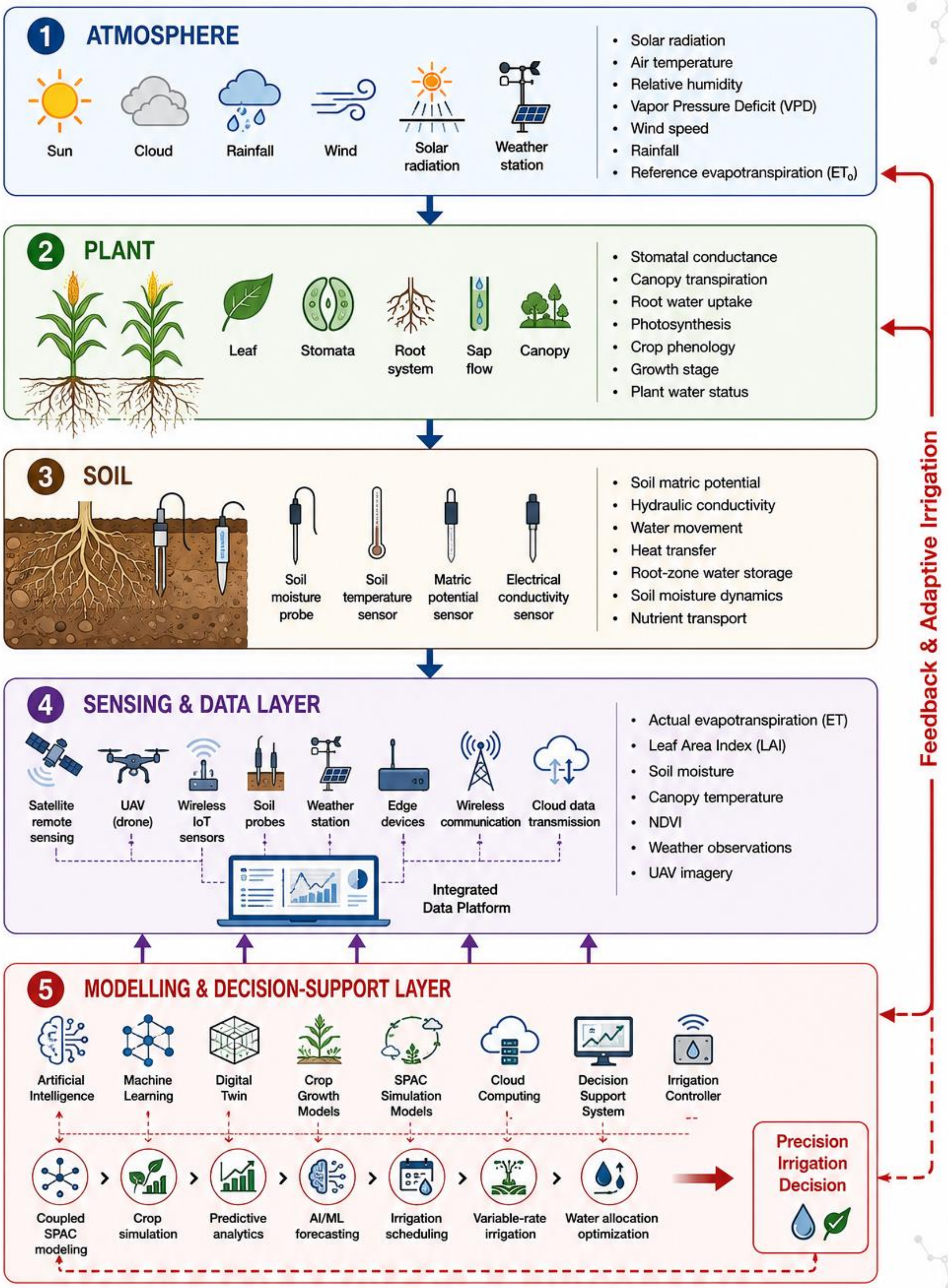

Fig 2: Conceptual framework of the coupled soil-plant-atmosphere (SPAC) system linking physical processes, sensing infrastructure, and model-based decision support for precision irrigation.

4. Thematic Classification of Included Studies

A total of 96 studies were included for synthesis, which can be organized into 5 different themes as represented in Figure 4 and listed in Table 3. More than 50% of the literature is made up of mechanistic SPAC or crop-hydrology models and Remote/Sensor Network studies, showing an early foundation in soil physics and hydrology while Machine Learning techniques are the fastest-growing domain in terms of publication over the last several years.

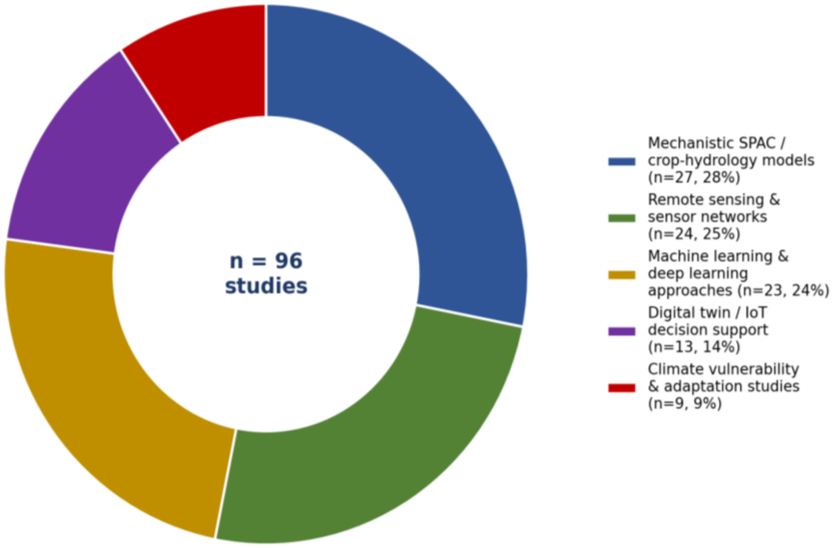

Fig 3: Thematic classification of studies included in the review (n = 96).

5. Literature Review and Thematic Analysis

5.1 Mechanistic Soil–Plant–Atmosphere Continuum and Crop-Hydrology Models

Coupled SPA modeling derives its theoretical foundation from viewing water movement in the soil-root-stem-leaf-atmosphere system as a continuous flow along a gradient of water potential.[7] Recent advancements have built on this idea in multiple ways. The CropSPAC model was created based on empirical research of winter wheat grown in Beijing. One of the main components of CropSPAC is crop-growth characteristics, such as leaf area index, height, root distribution and soil-plant-atmosphere water- and energy-transfer characteristics; when model predictions (based on unlinked models) were compared to experimental results for soil water storage following five types of irrigation, the coupled model offered a better fit (R^2 0.79-0.91) than did each of its unlinked component models for predicting soil water storage; thus, it is especially useful in conditions of deficit irrigation, where the link between drought stress and soil evaporation is greatest.[11]

Table 3: Summary of selected studies by thematic domain.

Thematic domain	No. of studies (n=96)	Representative approaches	Predominant crops/settings
Mechanistic SPAC / crop-hydrology models	27	CropSPAC, GEOSPACE, CFD-coupled canopy models, dual-source HDS-SPAC	Winter wheat, forest/orchard canopies, controlled plots
Remote sensing & sensor networks	24	Sentinel-1/2 SAR-optical fusion, SMAP/SMOS, ECOSTRESS/Landsat/VIIRS ET fusion, proximal sap-flow/electrophysiology sensors	Row crops, orchards, mixed cropland
Machine learning & deep learning	23	Random forest, SVM, CNN, LSTM/GRU, deep reinforcement learning	Field crops, greenhouse systems
Digital twin / IoT decision support	13	LoRa/IoT sensor fusion, edge-AI microcontrollers, mobile-app DSS	Orchards, smallholder plots, pilot commercial farms
Climate vulnerability & adaptation	9	Global/continental crop-water GCM assessments, FAO/UN vulnerability reporting	Global, continental and national scale

The GEOSPACE framework adopts a modular structure with a component-based approach where both infiltration and evapotranspiration are directly coupled, which produces greater accuracy in hydrological modeling. By ignoring the coupling between infiltration and evapotranspiration, hydrological modeling results in soil-water-potential profiles that are systematically biased. The coupling of SPAC modeling and CFD was undertaken to address the microclimate heterogeneity at the within-canopy and within-field scales. Thus, conventional SPAC modeling methods rely on one 'representative' data point for wind speed, air temperature, and radiation to conduct modeling of latent heat and sensible heat partitioning in spatially heterogeneous fields; these methods would misrepresent these and hence lead to errors in the modeling of heat transfer. Prior dual-source modeling methods, such as the hybrid dual source SPAC modeling method verified for the wheat cropping systems of northern China, had already provided a methodological basis for the separation of the energy balance components for soil and canopy, rather than treating as if they were two sides of a "twice-fold" sheet of paper.

In general agreement with this literature, it was found that linking the crop-growth model and the water/thermal transfer model improved prediction accuracy when compared to uncoupled models and solely empirical models of the water balance under conditions of limited water supply, especially where there is significant interaction between stress on the crop and soil evaporation rates. However, there are differences between the type of computational method used: CFD-coupled mechanistic ("highly parameterized") models provide very accurate predictions at the plot or field level; but require calibration data (e.g. root distribution, hydraulic conductivity curves, canopy architecture) which are rarely available at the scale of regional water management. Consequently, throughout this literature review there exists an ongoing conflict between mechanistic realism and operational scalability, which occurs multiple times within this literature.

5.2. Remote Sensing and Proximal Sensor Networks for Soil–Plant Water Status

Many authors have focused on the ways that state variables required for SPAC model simulations—specifically soil moisture, evaporation from soil and transpiration from vegetation, and the amount of water contained in vegetation canopy—can be observed at operationally useful spatial and temporal scales. For example, satellite-based soil moisture retrieval methods have progressed from passive microwave systems capable of acquiring data from around 25 km to synthetic aperture radar from the Sentinel-1 (SAR) satellite with spatial resolution of approximately 20 m, with additional fusion of Landsat data (optical indices to correct for vegetation).[14],[15] Additionally, machine-learning methods such as support vector regression (SVR), generalized regression neural networks (GRNN), and convolution neural network (CNN) have been shown to improve estimation accuracy compared to traditional scattering models (e.g., the Oh model) in agricultural areas with low vegetation density, although the performance of all methods degrades under high-density vegetation canopies.[16]

Evapotranspiration (ET) retrieval approaches have followed an analogous trajectory. The surface energy balance (SEB) technique using thermal infrared imagery is still the most widely used method for measuring ET at the field scale; however, because medium-resolution thermal infrared sensors often have a relatively low revisit rate, delivery of daily- to weekly-subfield ET products that can be used for irrigation scheduling will require using some combination of Landsat, Sentinel-2, ECOSTRESS, and VIIRS.[17] Researchers have confirmed through field validations that satellite-based soil moisture observations can produce significant reductions in irrigation water use.

The satellite record is complemented with sensing data collected in proximity (e.g., soil moisture probes, sap flow and dendrometric measures, canopy thermal imaging), as well as, more recently, methods to monitor plant water status directly using the PlantElectrophysiological Monitoring Method, using a classification model based on plant electrophysiological signals that can identify the transition of tomato plants from water stress to healthy conditions with up to 92% accuracy over a 30-minute observation period.[19] Across this body of literature, there is a consistent conclusion: no single technology can suffice as an indicator of plant water stress. For example, soil-based indicators do not reflect the true stress level of the plant in question. In addition, canopy thermal data may be confounded by variation in vapor pressure deficit, and the availability of satellite data is limited by spatial resolution and frequency of data acquisition, thereby supporting the need for multi-sensor data fusion systems as discussed in Section 5.4.

5.3. Machine Learning and Deep Learning for Irrigation Scheduling

The use of irrigation scheduling through machine-learning has been growing quickly from traditional regression analysis as well as trees-based ensemble methods towards deep learning and reinforcement learning methods. There are many published papers comparing various model types, but random forests and support vector machines have been used the most because they require less data to build than other types of models such as convolutional neural networks that work well with spatially structured input data like satellite or UAV images as well as recurrent architectures (long short-term memory & gated recurrent unit) that are best used with sequential time-series weather and soil moisture data.[20],[21] The review found that many of the studies that reported on machine-learning models reached accuracies of greater than 90% and that water savings were between 30% and 50% compared to traditional irrigation scheduling methods; however, it is important to note that the majority of these studies were based on controlled or semi-controlled field trials versus full-scale commercial applications.[10]

Reinforcement learning and deep reinforcement learning have received increasing interest by explicitly modelling the irrigation scheduling problem as a sequential (temporal) decision problem under uncertain circumstances and allowing the model to learn the scheduling policy directly from an environment simulation (or real-world experience) rather than through labelled examples. There are many reports of successful implementations all employing deep reinforcement learning, achieving both simultaneous water savings and yield increases (up to 41% and 26%, respectively, within a specific transformer-assisted structure), and demonstrating the potential to balance multiple (and sometimes competing) objectives such as water conservation, yield stability, and energy cost. However, several of the reviews express concern that reinforcement-learning techniques still have a very high data requirement, are still dependent on carefully constructed reward functions to avoid unexpected scheduling behaviour, and have little validation across more than one growing season or site.

One of the main points of the critiques in the literature on this subject is the selection of predictor variables. Most agricultural machine learning or deep learning irrigation model development relies almost exclusively on soil moisture-based indices while plant physiological indices (i.e., stem/leaf water potential, sap flow rate/stomatal conductance, temperature indices) have not had as much use as predictive inputs, notwithstanding the greater ability of those indices to represent plant stress. The lack of use of these plant indices is not due to their inferiority, but rather, attributed to the relatively high costs and lower degree of automation maturity of the sensors required to collect this information at scale. ^24 In addition, there is no clear consensus in the reviewed literature on which algorithm family to use, as performance rankings tend to vary by crop, climate, and the index being predicted; several authors discuss the lack of a standardized benchmark dataset as an impediment to the fair comparison of studies.

5.4. Digital Twins, IoT Architectures, and Integrated Decision Support

Recently there has been a growing interest in the concept of Digital Twin or closed-loop Decision Support Systems (DSS) that integrate Mechanistic Models, Sensors and Machine Learning. A Digital Twin is defined as an evolving virtual representation of a physical entity or location that is continuously updated with near real-time sensor data in order to simulate and forecast various scenarios, as well as suggest what irrigation methods/techniques should be employed. Many examples exist of utilizing sensor data in this manner. Specifically, by combining multi-source remote sensing (satellite imagery) and proximal IoT (soil sensors) sensor data along with machine learning - some results have shown accuracy gains when the same individual point (Geographical) and area-wide (Geographic) data types are fused instead of analyzed separately. For example, deep neural networks using both satellite 'ET' (Evapotranspiration) and soil moisture data have been able to classify irrigation systems at an overall field level with more than 90% accuracy.

The body of literature for low-cost, edge deployed implementations related to resource constrained farming systems is growing, and represents a key sub-area of this expanding field. Examples of using quantized neural networks running on microcontroller-class hardware (such as the ESP32) deployed on LoRa-based distributed sensor architectures have shown that irrigation decision support can be delivered with the model footprint of a few kilobytes, and with reasonably low power budgets. This suggests there are credible pathways for making precision irrigation available to smallholders. However, many of the studies reviewed consistently state that very little information available related to systematic energy-consumption profiling, long-term reliability of the systems in the field or TCO for low-cost deployments exist, creating limitations concerning how confidently pilot demonstration results will be extrapolated into sustained commercial/smallholder use.

Open source decision support systems have also been documented that couple mobile applications, LoRa weather stations, and ground sensors with adaptive statistical and/or machine learning forecasting in orchard settings. These examples show that digital twin architectures do not depend upon proprietary cloud-based architecture in order to provide irrigation recommendations to users at the site-specific level. Throughout this body of literature, there is strong consistency regarding the engineering bottleneck to scaling digital twin irrigation systems beyond single institution pilots is the lack of interoperability between data generated from mechanistic outputs from SPAC models, sensor data streams, and machine learning inference layers due to the lack of publicly available shared protocols.

5.5. Climate Vulnerability, Water Scarcity, and Adaptation Context

The fifth thematic cluster of literature connects climate variability to the wider world of environmental degradation. Globally and at a very local level, there will be differences in how agriculture and water use are affected by climate change. In the next decade, many experts believe that climate change will have a positive impact on many high-latitude areas and some parts of Africa and South America. However, in the long term, it has been predicted that there will be decreases in crop yields and production will increasingly require irrigation in areas that are experiencing water shortages.[6] The degree of uncertainty associated with these projections is believed to be more significantly influenced by the choice of global climate model, particularly for near-term projections, than by the emissions scenarios. This has direct implications for planning investment in precision irrigation infrastructure at local levels. Even if numerical estimates diverge, the qualitative picture produced by FAO and UN assessments is the same: Climate Change is causing an increase in both the number and severity of droughts and floods, whilst land degradation is lowering the water-retention capacity of soils, and the effects of both are felt disproportionately by smallholder, rainfed and low-income agricultural communities with the least adaptive capacity.[2],[3],[4] This body of literature provides the vulnerability context for the precision water management devices discussed in earlier sections; however, it also illustrates an issue: There are limited numbers of studies related to mechanistic, sensing and ML/DT (machine learning/deep transfer) technologies that evaluate their results against specific climate-related vulnerability indicators (such as frequency of droughts, rate of groundwater depletion, or smallholder adoption capacity) as opposed to generalized accuracy or water-saving metrics: this is discussed in more detail in Section 9.

6. Comparative Analysis of Previous Studies

Table 4 presents a structured comparison of representative studies drawn from each thematic domain, summarizing study context, methodology, principal findings, and limitations to support the critical synthesis presented in Sections 5 and 8.

7. Discussion

The collective nature of this review's five thematic strands indicates that while there is a technical advancement in the field, there continues to be an overall structural dislocation within the field. Mechanistic SPAC models remain the benchmark of water and energy system coupling and are used as benchmarks for validating either explicitly or implicitly all other sensing-based and AI-based approaches.; However, there are substantial challenges to using mechanistic SPAC models to validate new/unknown approaches to system efficiency due to the need for proper data and calibration in order to generate a representative model of the water and energy systems of interest, limiting most current valid implementation of mechanistic SPAC models to single, appropriately instrumented field sites.; In addition to the previously mentioned challenges of using mechanistic SPAC models; remote sensing and proximal sensor networks have significantly reduced the observational limitations previously encountered when attempting to have large scale deployments of mechanistic SPAC models, the additional observation capability and the ability of sensor integration have provided the best opportunity for deploying large scale mechanistic based SPAC models.

Research studies using machine-learning and deep-learning techniques present substantial evidence for water conservation ranging from 30-50%. There are numerous independent research studies across many crop systems that replicate these results. However, there is a lack of standardized benchmark datasets as well as an over-reliance on single-season and/or single-location trials, resulting in reported accuracy being indicative only of technical capability (how well the technique worked for the experiment) and not necessarily indicative of generalizability (how well this technique will work in other locations or in other seasons). This limitation is also present in other areas of the precision-agriculture ML literature, and it represents an area that has the greatest potential for maturation through community benchmark initiatives similar to those seen in other applied areas of ML.

IoTs are now the logical integration layer for all three strands of mechanistic modelling, sensing technologies, and machine learning, with evidence showing the technical feasibility of low-cost, low-power versions being good news for equitable deployment of this technology into practice. Unfortunately, this is arguably the most immature area in published literature, including that the majority of cited systems are pilot study, very few have been validated over multiple growing seasons, and even fewer provide information regarding total cost of ownership or energy budget, which would allow practitioners or decision makers to assess the feasibility of using these technologies in real-world applications. The climate-vulnerability literature provides a compelling rationale (i.e., a strong case) for urgent action; however, this literature and the technology literature are only weakly linked. For example, of the studies reviewed, very few explicitly correlate any modelling or sensing method with a specific climate-vulnerability indicator, resulting in the inability of the field to identify technology investment areas that would yield the greatest benefit to vulnerable populations.

Additionally, there is significant tension associated with the spatial and temporal scale of research. Research that uses continental and global data to assess the effects of climate change on crop water use indicates that the uncertainty in climate projections will increase as more variance is averaged together; it supports a concept known as the "spatial annulment phenomenon". Under such a scenario, the aggregate effects of different regions may mask the potential for more-pronounced regional trends. This suggests that precision irrigation technology that has been validated and deployed at the farm level may not be supported by the climate projections that are currently available at the regional or national level; thus, methodology associated with downscaling climatic information continues to be a nontrivial and not adequately addressed link between the literature surrounding climate vulnerability and precision irrigation technology. Thus, it appears that for the field to make progress in the near future, it will be necessary to consider integrative approaches to research rather than to continue to try to improve on each individual thematic area of research; specifically, that it is important to couple mechanistic realism to sensing, sensing to AI-based inference, and AI-based inference to the development of field-validated, cost-transparent deployment pathways that can be used by areas of climate vulnerability and where the need is the greatest.

8. Conclusion

This review integrated 96 peer-reviewed & institutional articles on mechanistic soil-plant-atmosphere continuum (SPAC) Modeling, remote & proximal sensing, machine learning-based irrigation scheduling, digital twins/IoT Decision Support, & the climate vulnerability context motivating this body of work. The literature clearly demonstrates technological advances within each of these areas: SPAC models increasingly capture the interaction between crop stress & soil-water dynamics with strong field validations; multi-satellite & proximal sensor fusions are closing historic gaps in observational data for soil moisture & evapotranspiration; machine learning approaches (especially deep & reinforcement learning) consistently demonstrate substantial water savings, while providing stable or improved yield outcomes.

Conversely, significant recurring limitations were noted: weak interoperability between mechanistic & data-driven model classes, lack of standardized benchmark datasets for objective cross-study comparisons, limited multi-season & multi-site validations of digital twins & reinforcement learning systems, inadequate documentation of energy/cost budgets associated with low cost deployments & persistent disconnect between the technical precision irrigation literature & the climate vulnerability literature.

For researchers the goal is developing and implementing hybrid, Physics-inspired Hybrid Machine Learning Architectures that maintain the interpretability & data efficiency associated with Mechanistic Small catchment Area Characterization (SPAC) models with the ability to leverage the Pattern Recognition powers of data driven approaches and investing in freely available multi-site benchmark datasets to help ensure that scheduling algorithms will be able to be compared on an equal basis across multiple sites. For practitioners & policy makers, today's research supports making early investment in low-cost Sensing and Edge Computing infrastructures to support the needs of Smallholder & Resource-Restricted Systems, rather than assuming that successful technologies developed and validated under high resource use will necessarily work in low-resource climate vulnerable settings, where they will most need to be utilized. Future research need to be conducted specifically to assess Precision Water Management Technologies against Climate Vulnerability Indicators rather than only against generic accuracy or water savings metrics; and prioritize Explainable Model Architectures that build the Trust required by Farmers & Institutions, to adopt the technology and ultimately enhance climate resilience through Precision Water Management. Integrated Soil-Plant-Atmosphere Modeling using AI-based Decision support tools, integrated with Sensors, lead the path forward to achieving climate-resilient Precision Water Management; if the field can address integration, validation, and equity gaps identified in this report.

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